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On the Dynamics of Contributions and Beliefs in Repeated Public Good Games*

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Abstract

Using data from a repeated public good game, I conduct a Granger causality test and find that contributions and beliefs about the contributions of others decline together, with neither variable leading the other. As a result, I model contributions and beliefs using a system of simultaneous equations. Estimating the system provides evidence on the magnitude of the projection bias. Since contributions and beliefs move together, indicating that current and/or past values of one series are not useful for predicting future values of the other, I develop and test the hypothesis that contribution heterogeneity predicts changes in average contributions. I find support for my hypothesis using data from a variety of public good game experiments (with and without belief elicitation; fixed and random matching).

JEL Classification: C32; C33; C36; C91; H41

Keywords: Public Good Game; Contributions; Beliefs; Granger Causality; Simultaneity; Simultaneous Equations

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1 Introduction

The convention in the literature on conditional cooperation in repeated public good games is to model contributions as a function of beliefs (Croson, 2007; Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010) and beliefs as a function of variables from the previous round (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010), implicitly assuming that in each round, beliefs are exogenous to contribution decisions. Some researchers recognize the potential endogeneity of beliefs in economic experiments and use various instrumental variables (IV) strategies for estimating the causal effects of beliefs (Bicchieri and Xiao, 2009; Costa-Gomes et al., 2010; Smith, 2013), but most do so in one-shot games (Bicchieri and Xiao, 2009; Costa-Gomes et al., 2010). Smith (2013) studies a repeated public good game, but does not suggest how the dynamics of contributions and beliefs should be modeled. Instead, he focuses on obtaining estimates of the contemporaneous causal effect of beliefs on contributions. Determining the appropriate way of modeling the dynamics of contributions and beliefs is the main objective of this paper.

Beliefs are potentially endogenous for a number of reasons. First, they are elicited by asking subjects to state their beliefs, so they are likely measured with error. Second, regressions of contributions on beliefs may suffer from omitted-variables biases. One possible omitted variable is a measure of adherence to social norms, the idea being that people who adhere to social norms will both contribute more and believe that others will contribute more.[1] Related to this, a third source of endogeneity is simultaneity between contributions and beliefs, where both variables move together over time, without either directly causing the other.

I focus on developing a better understanding of the simultaneity between contributions and beliefs. However, my estimation strategy addresses all three sources of endogeneity mentioned above. I initially examine the dynamics of contributions and beliefs while making

[1]If adherence to perceived social norms is time invariant, it can be captured using subject-specific fixed effects. Unfortunately, such a strategy will fail to address any tendency for adherence to social norms to change with repetition of the game. It seems that while subjects might start out highly willing to adhere to social norms, their resolve may diminish after they start observing the free riding of others.

minimal ex ante assumptions about how either variable is determined. Specifically, I use a Granger causality test (Granger, 1969) to inform how I specify contributions and beliefs. The Granger causality test indicates that contributions and beliefs decline together, with neither variable leading the other. In light of this finding, I model contributions and beliefs using a system of simultaneous equations.

Estimating the system provides causal estimates of how contributions and beliefs are determined. The simultaneous equations model is simple and straightforward, but to my knowledge, such a method has not previously been used for analyzing data from a repeated game experiment. As such, my strategy provides a new reduced-form alternative to estimating the joint determination of actions and beliefs using structural methods, as in Bellamare et al. (2008) and Bellamare et al. (2011).

The finding that contributions and beliefs move together challenges previous theories about the dynamics of contributions assuming that in each round, subjects choose contributions based on already determined beliefs (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010). As a result, I develop and test an alternative hypothesis on the dynamics of contributions: changes in average contributions are negatively related to contribution heterogeneity in the previous round. I present empirical support for my hypothesis.

The main analysis is conducted using the data from Smith (2013), who reports results from a 20 round repeated public good game. Other similar experiments (Croson, 2007; Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010) tend to be ten round games, and a longer panel of data is always desirable for conducting time series analysis. Even so, I test my hypothesis that changes in average contributions are negatively related to contribution heterogeneity using a variety of other data sets (Isaac and Walker, 1988; Andreoni, 1995; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010) from experiments with and without belief elicitation, and using fixed and random matching. The support for my hypothesis is robust across all the data sets.

I contribute to the literature on repeated public good games in a variety of ways. First, the Granger causality test and estimates from the simultaneous equations model provide insight on the determination of contributions and beliefs. There is simultaneity between the two variables that should be reflected in dynamic models of behavior in such games. Second, my estimates provide the first evidence of which I am aware on the magnitude of the "projection bias," which is the tendency for actions to cause beliefs because people project their behavior on to others. I estimate that unit increases in contributions increase beliefs by 0.15 units. Finally, my results on the relationship between changes in average contributions and contribution heterogeneity provide evidence in favor of a new view on what determines the dynamics of contributions.

My finding on the effect of contribution heterogeneity also complements the empirical literature reporting that population heterogeneity reduces cooperation (Alesina et al., 1999; Alesina and La Ferrara, 2000). Previous experiments (Chen and Li, 2009) demonstrate that people who are different from one another show lower levels of altruism and positive reciprocity toward each other. However, if different people also contribute different amounts due to differences in individual characteristics, then the negative relationship between contribution heterogeneity and average cooperation also helps to explain why cooperation is reduced in environments where population heterogeneity is high.

2 The Experiment

Instead of running a new experiment, for the main analysis, I re-examine the data of Smith (2013), who conducted a 20 round game eliciting the beliefs of subjects in each round. The primary difference between his experiment and others (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010) is the length of the panel.[2] For a full explanation of the experiment, please consult Smith (2013).

The experiment was a repeated, linear public good game with fixed matching in groups of

[2]The cited experiments are all 10 rounds. Croson (2007) has subjects play two 10 round games, creating a structural break. A longer panel is always desirable for time series analysis.

four. In each of 20 rounds, subjects were given endowments of 10 lab dollars (LD) and chose contributions to the "group account" (the public good), keeping the rest of the endowments for themselves.[3] As proceeds from the group account, each subject received 0.5 times the sum of contributions. Thus, the payoffs were:

$$\pi_i = 10 - contribution_i + 0.5 \sum_{j=1}^{4} contribution_j \tag{1}$$

where $contribution_i$ was the contribution of subject i and subject i's group members are indexed by j.

Subjects reported their beliefs by "guessing" the average amounts contributed by the other three members of their groups. The belief elicitation was incentive compatible, but the payments for belief accuracy were small compared to the payoffs from the public good game so that strategically stating beliefs different from true beliefs provided minimal hedging against receiving a low payoff in the public good game.

After each round, subjects were told the average amounts contributed by the other members of their groups, and their payoffs from the public good game and for the accuracy of their guesses. At the end, the payoffs were converted to USD and added to a $5 show-up fee.

3 Main Results

The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). A total of 64 subjects participated in the experiment, generating 1,280 observations.[4] The experiment lasted 45 minutes and average total earnings were $19.51. Overall, the average contribution was 3.94 (std. dev. 2.98) and the average belief was 4.19 (std. dev. 1.91). Average contributions and beliefs in each round are plotted in Figure 1.

Figure 1: Trends of Average Contributions and Beliefs

[3] LD were later converted to USD at a rate of 1 LD = 0.05 USD.

[4] There were six sessions: four with 12 subjects and two with eight.

3.1 Granger Causality Test

Conventional wisdom (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010) is that subjects begin each round with well-formed beliefs about what others will contribute. Based on these beliefs, they choose contributions reflecting preferences for contributing less than others. They then observe the average contributions of others and update their beliefs prior to the start of the next round. According to this view, contributions will lead the decline of beliefs because preferences for contributing less than others initiate the decline of contributions, and beliefs simply follow.

However, if contributions and beliefs are jointly determined by variables from the previous round, and by each other, they will decline together. To explore this possibility empirically, I follow the test of Granger causality (Granger, 1969) described by Greene (2012, page 318).[5] I perform the estimation using the method of Arellano and Bond (1991), which is suggested by Wooldridge (2010, pages 371-374) for estimating autoregressive models because fixed effects estimation is known to be inconsistent (Nickell, 1981).

I begin by building a dynamically complete model of contributions (see Table 1).[6] Specification (I) regresses contributions on contributions in the previous round, the average contributions of others in the previous round and the round. The average contributions of others in the previous round are included in light of prior literature finding that the previous contributions of others affect behavior (Fischbacher et al., 2001; Keser and van Winden, 2000; Croson et al., 2005; Bardsley and Moffatt, 2007; Ashley et al., 2010; Ferraro and Vossler, 2010). Current beliefs are not included because testing for Granger causality involves determining if past beliefs add explanatory power to a dynamically complete model of contributions.

Table 1: Granger Causality Test

[5] Hurlin and Venet (2001) provide a discussion about Granger causality tests in panel data models. In particular, they point out that there are no special issues associated with implementing the test in a panel.

[6] A model is dynamically complete when additional lags of the dependent variable are not statistically significant. I lose two observations per subject: one due to the inclusion of first lags in the model and a second because the Arellano-Bond method estimates the model in first differences.

Unit increases in contributions in the previous round and in the average contributions of others in the previous round are associated with 0.17 and 0.22 unit increases in contributions. Repetition has a small, negative effect. For consistency, the Arellano-Bond (AB) estimator requires that there is no second order autocorrelation among the errors of the first differenced model (Arellano and Bond, 1991). An AB test ($p = 0.40$) does not suggest such correlation.

An additional lag of contributions is not significant when added to specification (I), indicating that the model is dynamically complete. In specification (II), the first lag of beliefs is not significant. Thus, I fail to find evidence that beliefs Granger cause contributions.

Specification (III) is the dynamically complete model of beliefs. In specification (IV), the first lag of contributions is not significant when added to specification (III), failing to provide evidence that contributions Granger cause beliefs. Therefore, neither of contributions nor beliefs Granger causes the other. Rather, the Granger causality test indicates that the two variables decline together, without either one leading the other.

3.2 Modeling Contributions and Beliefs

In light of the Granger causality test indicating that contributions and beliefs decline together, I model the variables using the following system of simultaneous equations:

$$contribution = \beta_{10} + \gamma_1 belief + \beta_{11} contribution_{-1} + \beta_{12} round + \varepsilon_1 \tag{2}$$

$$belief = \beta_{20} + \gamma_2 contribution + \beta_{21} belief_{-1} + \beta_{22} average\,others_{-1} + \beta_{23} round + \varepsilon_2 \tag{3}$$

Modeling contributions as a function of beliefs and past contributions is consistent with previous literature (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Smith, 2013). In contrast, where as the previous literature (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Smith, 2013) models beliefs as a function of past beliefs and the average contributions of others in the previous round, here I add contributions in order to estimate the magnitude of the projection bias, and capture any tendency for contributions and beliefs to move together.

To demonstrate the effects of neglecting the simultaneity between contributions and beliefs, I first estimate each equation using OLS (specifications (I) and (II) in Table 2).[7] In specification (I), beliefs have a large effect on contributions, consistent with previous literature (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010; Smith, 2013). In specification (II), contributions have an important effect on beliefs, suggesting that the projection bias is significant, but at this point, it is not clear to what extent the results are due to the unaddressed simultaneity.

Table 2: Simultaneous Equations Model

Specifications (III) and (IV) are estimated using 2SLS and address the simultaneity between contributions and beliefs. In specification (III), the variables omitted from equation (2) ($belief_{-1}$ and $average\,others_{-1}$) are used as instruments for beliefs. Consistent with Smith (2013), the causal effect of beliefs on contributions (0.39) is much smaller than suggested by the OLS estimate (0.77) in specification (I). As far as specification tests, a Hausman test ($p = 0.00$) indicates that beliefs are highly endogenous, while Sargan ($p = 0.17$) and Basmann ($p = 0.19$) tests fail to reject the null hypothesis that $belief_{-1}$ and $average\,others_{-1}$ are valid instruments for beliefs. Finally, the first-stage F-statistic (165.08) indicates that the instruments are not weak.

In specification (IV), the variable omitted from equation (3) ($contribution_{-1}$) is used as an instrument for contributions. The estimated effect of contributions on beliefs provides evidence on the magnitude of the projection bias. Specifically, unit increases in contributions increase beliefs by 0.15. Thus, an increase in *contribution* from 3 to 5 is estimated to increase $belief$ by $0.15 * (5 - 3) = 0.30$ (from 4 to 4.3, for example). The projection bias is smaller in magnitude than the causal effect of beliefs on contributions (0.39), but is still indicative of contributions and beliefs moving together over time.

[7]Subject dummies control for subject-specific fixed effects. Smith (2013) reports that this gives very similar results to the AB method, which cannot be used within a system of equations. See Merrett (2012) for a more detailed analysis of the pros and cons of different estimators.

For specification (IV), a Hausman test ($p = 0.67$) fails to reject the null hypothesis that contributions are exogenous, suggesting that OLS (specification (II)) provides a reasonably accurate estimate of the projection bias. The equation is just-identified, so tests (Sargan and Basmann) of overidentifying assumptions are not possible, but specification (IV) from Table 1 indicates that lagged contributions do not affect beliefs, suggesting that they are a valid instrument for contributions. The F-statistic indicates that lagged contributions are not a weak instrument.

I also estimated the system using 3SLS (the efficient estimator). The standard errors are smaller than in specifications (III) and (IV), but the coefficients are nearly identical.[8]

3.3 Predicting Changes in Average Contributions

Evidence that contributions and beliefs decline together challenges theories on the dynamics of contributions and beliefs assuming that beliefs are exogenous to contribution decisions (Neugebauer et al., 2009; Fischbacher and Gaechter, 2010). But if one wants to avoid making such assumptions, how should contributions be modeled in way that is useful for making predictions about the path of contributions? For motivating my hypothesis, I turn to research on how contributions relate to the previous contributions of others (Fischbacher et al., 2001; Keser and van Winden, 2000; Croson et al., 2005; Bardsley and Moffatt, 2007; Ashley et al., 2010; Ferraro and Vossler, 2010).

Ashley et al. (2010) study the effects of deviating from the average contribution of one's group members in the previous round. Subjects who contributed more than the average tend to reduce their contributions. Subjects who contributed less than the average tend to make similar contributions in the current round. I build on the work of Ashley et al. (2010) by using their results to inform my hypothesis about how average contributions change over time. In light of their results, I expect that changes in average contributions will be decreasing in contribution heterogeneity. Basically, if within a particular group, all members contribute

[8]Results available upon request.

the same amount in a given round, I expect that the average contribution will be about the same in the next round because no one will significantly change her contribution. If, on the other hand, different group members contribute different amounts, I expect that the average contribution will be lower in the next round because some subjects will reduce their contributions and others will contribute similar amounts to those that they contributed in the prior round.

I test my hypothesis by regressing changes in average contributions on contribution heterogeneity in the previous round, which I measure by calculating the standard deviation of the four individual contributions for each group in each round. The regression results are reported in Table 3. The results of OLS regressions are given, but random and fixed effects models give very similar results. There is no need to adjust the standard errors for clustering at the group level because group level variables are the units of analysis. The standard errors are robust to heteroskedasticity and autocorrelation.

Table 3: Regressions of Changes in Average Contributions

In specification (I), unit increases in the standard deviations of contributions in the previous round are associated with 0.14 unit decreases in the change in average contributions. Therefore, average contributions decrease more when contribution heterogeneity is high, as expected. For the sake of comparing the contribution heterogeneity-based model to a belief-based model, specification (II) regresses changes in average contributions on changes in average beliefs. There is a positive relationship between changes in average beliefs and changes in average contributions, but the effect is not significant. Thus, changes in contributions are better predicted by contribution heterogeneity than by changes in beliefs.

In specification (III), just the round is included, but there is no significant effect. In additional specifications (not reported, but available upon request), I find that the standard deviations of contributions are also unrelated to the round, indicating that the relationship between changes in average contributions and lagged standard deviations of contributions is not simply an artifact of both variables being related to the round. Finally, specification

(IV) includes all three explanatory variables; the relationship between changes in average contributions and lagged standard deviations of contributions is robust.

4 Other Data Sets

To determine the generalizability of my findings, I first replicated my main results using the data from Gaechter and Renner (2010), who ran a ten round repeated public good game with fixed groups of four.[9] Their experiment was on the effects of eliciting incentivized and non-incentivized beliefs, and consisted of three treatments: incentivized belief elicitation, non-incentivized belief elicitation and no belief elicitation.

Using the data from the first two treatments, I found that with both belief elicitation methods, the Granger causality and simultaneous equations model results were qualitatively similar to my main results, by that the estimators did not perform quite as well with the shorter panel (ten rounds as opposed to 20).[10] Specifically, conducting the Granger causality tests, there were a couple of cases where the evidence that contributions and/or beliefs follow an autoregressive process (depend on their lagged values) was not significant. As a result, when estimating the simultaneous equations models, lagged contributions were typically a weak instrument for contributions.[11] This highlights the advantages of collecting a 20 round panel of data instead of the more conventional ten rounds.

In contrast, the evidence on the relationship between changes in average contributions and contribution heterogeneity (presented in Table 4) is very consistent with my main results. Specification (I) uses the data from the incentivized beliefs treatment and indicates that unit increases in the standard deviations of contributions in the previous round are associated with 0.20 unit decreases in average contributions. Specification (II) gives a very similar result when beliefs are not incentivized. In specification (III), I estimate the relationship

[9]The marginal per capita return (MPCR) from the public good was 0.4 and subjects were endowed with 20 tokens at the start of each round.

[10]All of these results are available upon request.

[11]Similar challenges arise when I truncate the Smith (2013) data at ten rounds.

when there is no belief elicitation and find that the effect of contribution heterogeneity is slightly larger in magnitude.

Table 4: Regressions of Changes in Average Contributions - Data from Gaechter and Renner (2010)

Motivated by the finding that the relationship between changes in average contributions and contribution heterogeneity is especially strong when there is no belief elicitation, I subsequently estimated the effect of contribution heterogeneity using the data from Isaac and Walker (1988), who studied the effects of endowment levels (10, 25 or 62 tokens), MPCRs (0.30 or 0.75) and group sizes (4 or 10 subjects). Subjects participated in two "sequences" of decision-making, each a ten round game with fixed groups.

In specification (I) in Table 5, the standard deviation of contributions in the previous round has a significant negative effect on changes in average contributions. The effects of the experimental conditions (endowments, MPCRs, group sizes and the sequence) are not significant, emphasizing the unique predictive power of contribution heterogeneity.

Table 5: Regressions of Changes in Average Contributions - Data from Isaac and Walker (1988), Fischbacher and Gaechter (2010), and Andreoni (1995)

Many public good game experiments use random matching in each round instead of fixed matching, which raises the question of whether my contribution heterogeneity hypothesis can be adapted for such environments. Using the data from Fischbacher and Gaechter (2010), I tested the following variant of the hypothesis: instead of calculating the standard deviations of contributions and changes in average contributions at the group level, I calculated them at the session level. This reduces the number of observations to one from each round in each session, but I thought that it would be informative to see what would happen.

In specification (II), contribution heterogeneity once again has a negative effect on changes in average contributions, indicating that the hypothesis has good predictive power with random matching as well. Finally, I tested the hypothesis using the data from Andreoni (1995), who examined the effects of positive versus negative framing. Since Andreoni (1995) conducted only four sessions of his ten round game, specification (III) has only 36 observations, but the effect of contribution heterogeneity is still (weakly) significant. The magnitude of the effect is also very much in line with the previous results, indicating that contribution heterogeneity is consistently a good predictor of the dynamics of average contributions.

5 Summary

In light of a Granger causality test indicating that there is simultaneity between contributions and beliefs, I model the variables using a system of simultaneous equations. Estimating the system provides evidence on the magnitude of the projection bias. Specifically, I find that unit increases in contributions increase beliefs by 0.15 units. The simultaneous equations model results also provide evidence on the joint determination of contributions and beliefs that challenges previous theories on the dynamics of contributions assuming that subjects choose contributions based on already determined beliefs. As a result, I develop and test an alternative hypothesis that the dynamics of contributions are negatively related to contribution heterogeneity, for which I find strong support.

I subsequently conducted analysis using a variety of other data sets (Isaac and Walker, 1988; Andreoni, 1995; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010). I find that the Granger causality and simultaneous equations model results are much cleaner with a 20 round panel as opposed to ten, providing support for conducting more repetitions of the game than the standard ten rounds. However, the evidence that the dynamics of contributions are predicted by contribution heterogeneity is consistent across many conditions: incentivized versus non-incentivized belief elicitation, belief elicitation versus no belief elicitation, and fixed versus random matching. As such, the support for my hypothesis that contribution heterogeneity has a central role in determining the dynamics of average contributions is quite robust.

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Table 1: Granger Causality Test

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*contribution*	*belief*	*belief*
$contribution_{-1}$	0.17***	0.17***	-	0.04
	(0.05)	(0.06)		(0.02)
$belief_{-1}$	-	0.00	0.17***	0.14***
		(0.09)	(0.03)	(0.04)
$average\,others_{-1}$	0.22**	0.23***	0.54***	0.54***
	(0.09)	(0.09)	(0.05)	(0.05)
round	-0.07***	-0.07***	-0.02***	-0.02**
	(0.02)	(0.02)	(0.01)	(0.01)
constant	3.09***	3.09***	1.50***	1.44***
	(0.59)	(0.69)	(0.34)	(0.31)
subjects	64	64	64	64
rounds	2-20	2-20	2-20	2-20
n	1,152	1,152	1,152	1,152
AB test p	0.40	0.43	0.66	0.63

Notes: Standard errors adjusted for clustering at the subject level are reported in parentheses. Adjusting for clustering at a different level (for example, at the group level) is not possible with this estimator.

***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 2: Simultaneous Equations Model

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*belief*	*contribution*	*belief*
contribution	-	0.18***	-	0.15*
		(0.02)		(0.08)
belief	0.77***	-	0.39***	-
	(0.08)		(0.09)	
$contribution_{-1}$	0.12**	-	0.17***	-
	(0.04)		(0.04)	
$belief_{-1}$	-	0.18***	-	0.18***
		(0.03)		(0.03)
$average\,others_{-1}$	-	0.53***	-	0.54***
		(0.04)		(0.03)
round	-0.03*	0.00	-0.06***	0.00
	(0.01)	(0.01)	(0.02)	(0.01)
constant	0.53	0.57***	2.27***	0.69
	(0.32)	(0.19)	(0.65)	(0.55)
subject dummies	yes	yes	yes	yes
method	OLS	OLS	2SLS	2SLS
subjects	64	64	64	64
rounds	2-20	2-20	2-20	2-20
n	1,216	1,216	1,216	1,216
R^2	0.29	0.79	0.55	0.84
Hausman p	-	-	0.00	0.67
Sargan p	-	-	0.17	-
Basmann p	-	-	0.19	-
1st stage F-stat	-	-	165.08	13.27

Notes: Standard errors adjusted for clustering at the group level are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 3: Regressions of Changes in Average Contributions

	(I)	(II)	(III)	(IV)
$std.\,dev.\,of\,contributions_{-1}$	-0.14**	-	-	-0.14**
	(0.07)			(0.07)
$\triangle\,average\,belief$	-	0.11	-	0.12
		(0.09)		(0.10)
$round$	-	-	-0.01	-0.01
			(0.01)	(0.01)
$constant$	0.22	-0.10	0.00	0.29
	(0.16)	(0.07)	(0.15)	(0.19)
groups	16	16	16	16
rounds	2-20	2-20	2-20	2-20
n	304	304	304	304
R^2	0.02	0.01	0.00	0.02

Notes: Standard errors robust to heteroskedasticity and autocorrelation are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 4: Regressions of Changes in Average Contributions - Data from Gaechter and Renner (2010)

	(I)	(II)	(III)
$std.\,dev.\,of\,contributions_{-1}$	-0.20***	-0.23***	-0.30***
	(0.07)	(0.07)	(0.08)
$\triangle\,average\,belief$	0.24*	0.13	-
	(0.14)	(0.08)	
$round$	-0.06	-0.04	-0.04
	(0.06)	(0.08)	(0.07)
$constant$	1.00*	0.94	1.15
	(0.54)	(0.74)	(0.73)
treatment	incentivized beliefs	non-incentivized beliefs	no belief elicitation
groups	16	17	18
rounds	2-10	2-10	2-10
n	144	153	162
R^2	0.08	0.09	0.08

Notes: Standard errors robust to heteroskedasticity and autocorrelation are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 5: Regressions of Changes in Average Contributions - Data from Isaac and Walker (1988), Fischbacher and Gaechter (2010), and Andreoni (1995)

	(I)	(II)	(III)
$std.\,dev.\,of\,contributions_{-1}$	-0.33***	-0.34***	-0.42*
	(0.12)	(0.09)	(0.23)
$\triangle\,average\,belief$	-	0.32*	-
		(0.16)	
round	-0.01*	-0.07	-0.34
	(0.00)	(0.05)	(0.27)
endowment (in tokens)	0.00	-	-
	(0.00)		
high mpcr (1 or 0)	0.03	-	-
	(0.04)		
large group (1 or 0)	0.00	-	-
	(0.05)		
sequence (1 or 2)	-0.01	-	-
	(0.02)		
negative frame (1 or 0)	-	-	-1.21
			(1.42)
constant	0.13	1.92**	8.77
	(0.12)	(0.79)	(5.53)
data	IW1988	FG2010	A1995
groups	12	-	-
sessions	-	6	4
rounds	2-10	2-10	2-10
sequences	2	1	1
n	216	54	36
R^2	0.07	0.20	0.08

Notes: Standard errors robust to heteroskedasticity and autocorrelation are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Figure 1: Trends of Average Contributions and Beliefs